



Batch process monitoring based on support vector data description method

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ABSTRACT

Process monitoring can be considered as a one-class classification problem, the aim of which is to differentiate the normal data samples from the faulty ones. This paper introduces an efficient one-class classification method for batch process monitoring, which is called support vector data description (SVDD). Different from the traditional data description method such as principal component analysis (PCA) and partial least squares (PLS), SVDD has no Gaussian assumption of the process data, and is also effective for nonlinear process modeling. Furthermore, SVDD only incorporates a quadratic optimization step, which makes it easy for practical implementation. Based on the basic SVDD batch process monitoring approach, the method is further extended to multiphase and multimode batch processes. Two case studies are provided to evaluate the monitoring performance of the proposed methods.

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1. Introduction

Nowadays, batch processes play an important role in producing low volume and high value-added chemical and biochemical products. The production cost has been reduced, while the batch product quality is required to improve over the recent years. To this end, advanced process quality control and monitoring techniques have become popular in recent years. Particularly, the data-based statistical monitoring approach has been one of the main research topics in batch processes. By extracting useful information from the recorded process dataset, the operation condition and the product quality of the process can be monitored and predicted.

For batch process monitoring, the conventional multivariate statistical process control (MSPC) methods that have been widely used for continuous process monitoring have been extended to batch processes. Multiway counterparts of the traditional methods have been developed, such as multiway principal component analysis (MPCA), multiway partial least squares (MPLS) and their variations [1–13]. Due to the multiphase behavior which is very common in most batch processes, several multiphase monitoring approaches have also been proposed, such as sub-PCA model based method, phase or stage PLS based method, phase-based batch process monitoring and analysis approach [14–22]. However, the data description of most PCA and PLS related methods is under assump-

tions that the data distribution is Gaussian and the correlation between different process variables is linear. When the distribution of the batch process data is non-Gaussian, or the relationship between their variables is nonlinear, monitoring approaches based on PCA/PLS may not function well.

Some related batch process monitoring methods have been developed to tackle either the non-Gaussian distribution or the nonlinear nature of the process data. For example, by extending the independent component analysis (ICA) method to its multiway form, the multiway ICA method can successfully catch the non-Gaussian data information in the batch process [23–30]. However, there exist several drawbacks of the multiway ICA based method which makes it inefficient for batch process monitoring. First, multiway ICA may lead to different solutions due to its random initialization, which may give unstable monitoring results. Second, how to select the number of independent components is still an open question, which may greatly influence the final monitoring result. Furthermore, the data description of the monitoring statistic and the estimation of its control limit are based on the kernel density estimation method, which is computationally expensive. For nonlinear batch process monitoring, traditional multiway PCA and PLS methods have been extended to their nonlinear forms, such as multiway kernel PCA, and multiway kernel PLS [31–36]. By introducing the nonlinear transformation function, the nonlinear behavior of the batch process data can be incorporated into the monitoring method. However, process monitoring based on these nonlinear multiway methods is typically under the Gaussian assumption. Recently, to simultaneously address the non-Gaussian

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